Deep Reinforcement Learning in Mixture of Experts Control System for Blind Wheeled-Legged Quadrupedal Locomotion

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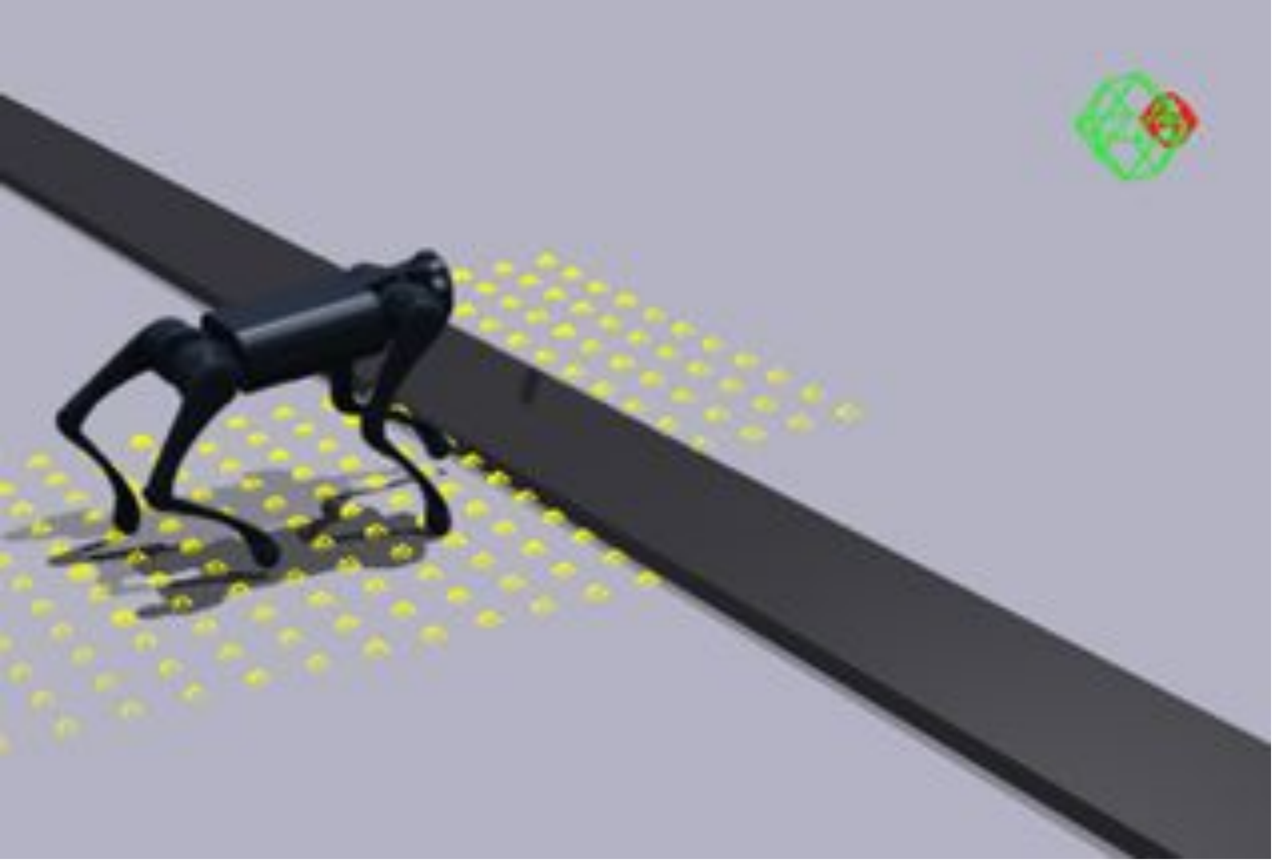
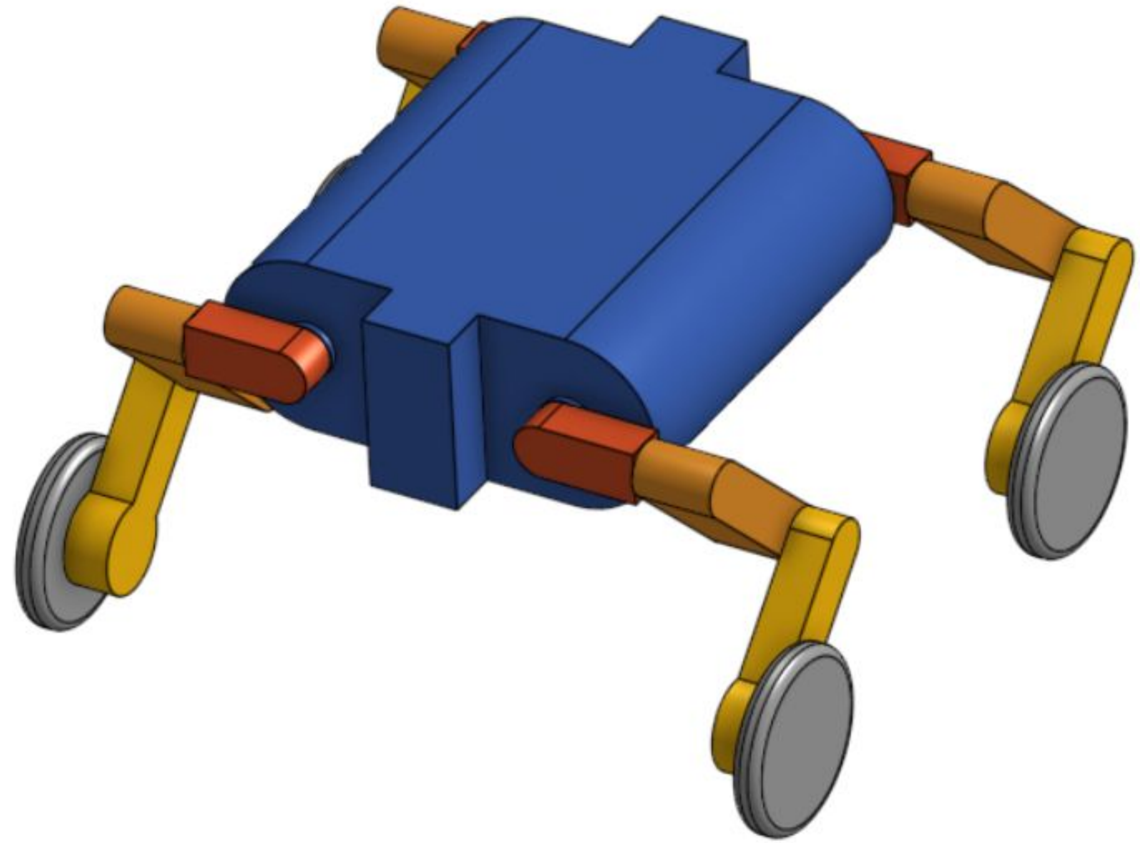
Overview

Wheeled-Legged Locomotion





Research Objective:

Blind Locomotion

S. Chamorro et al., "Reinforcement Learning for Blind Stair Climbing with Legged and Wheeled-Legged Robots," ArXiv, vol. abs/2402.06143, 2024.




JPL

Current Control Methods

Model Predictive Control

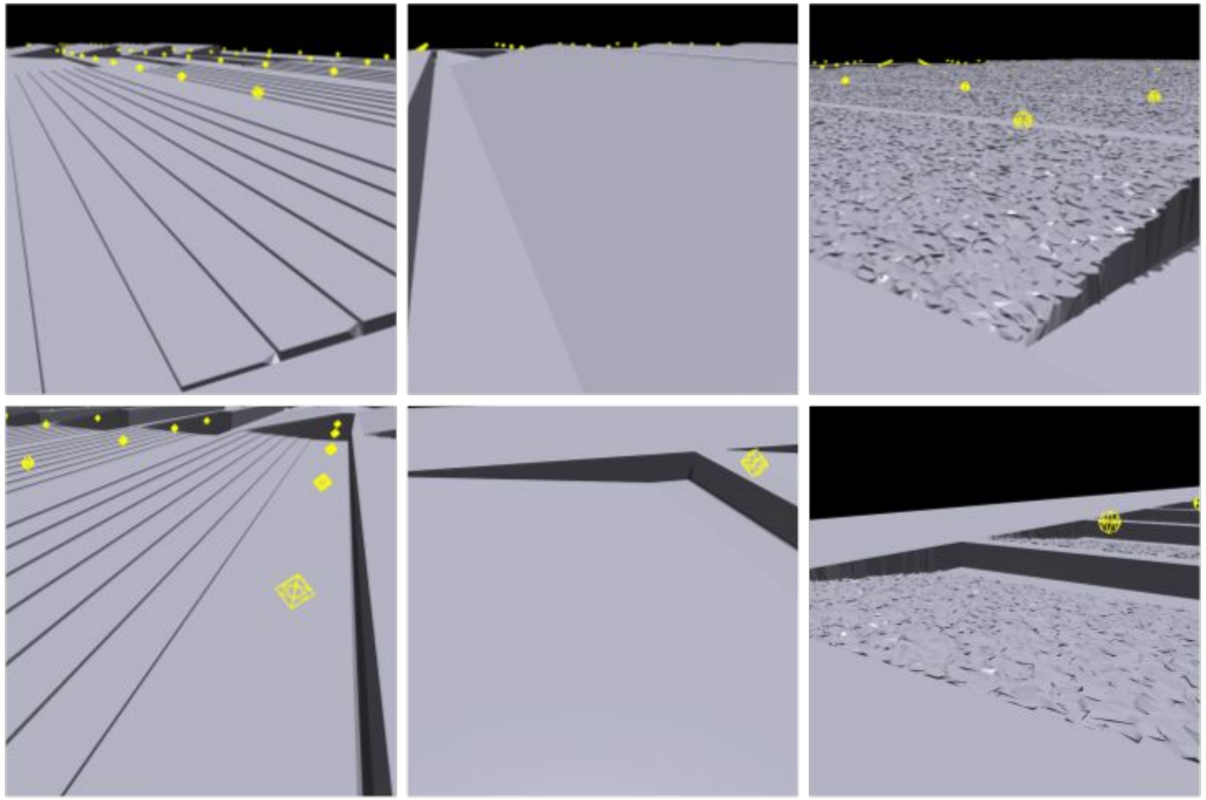
- Very Difficult Without Accurate State Estimation

Reinforcement Learning

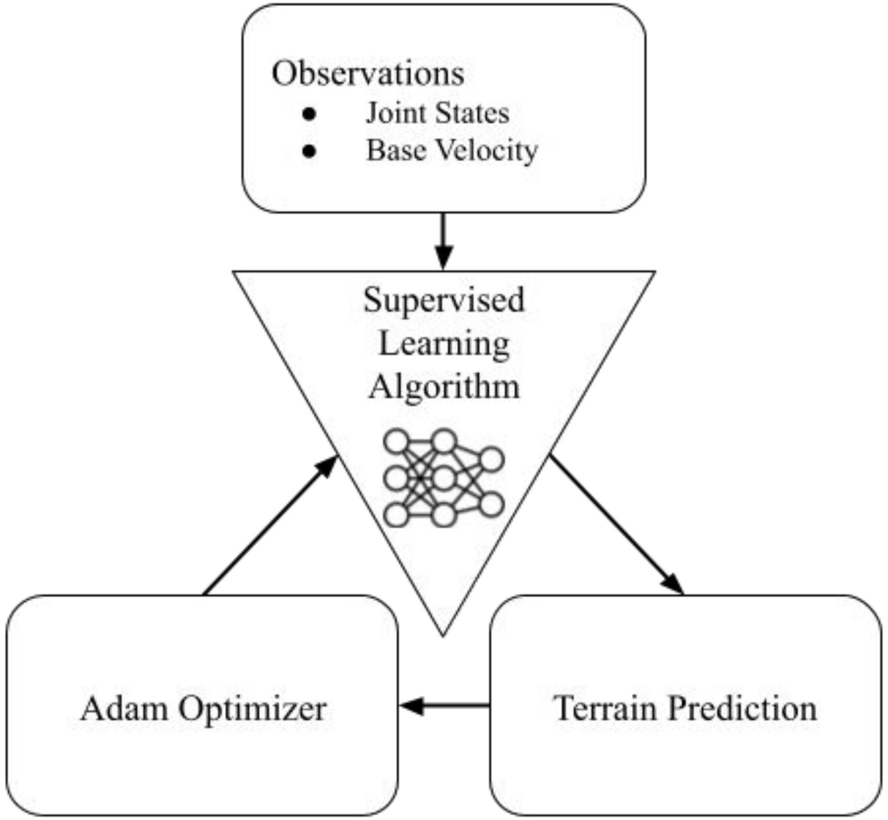
- Functional on Single Terrain When Blind

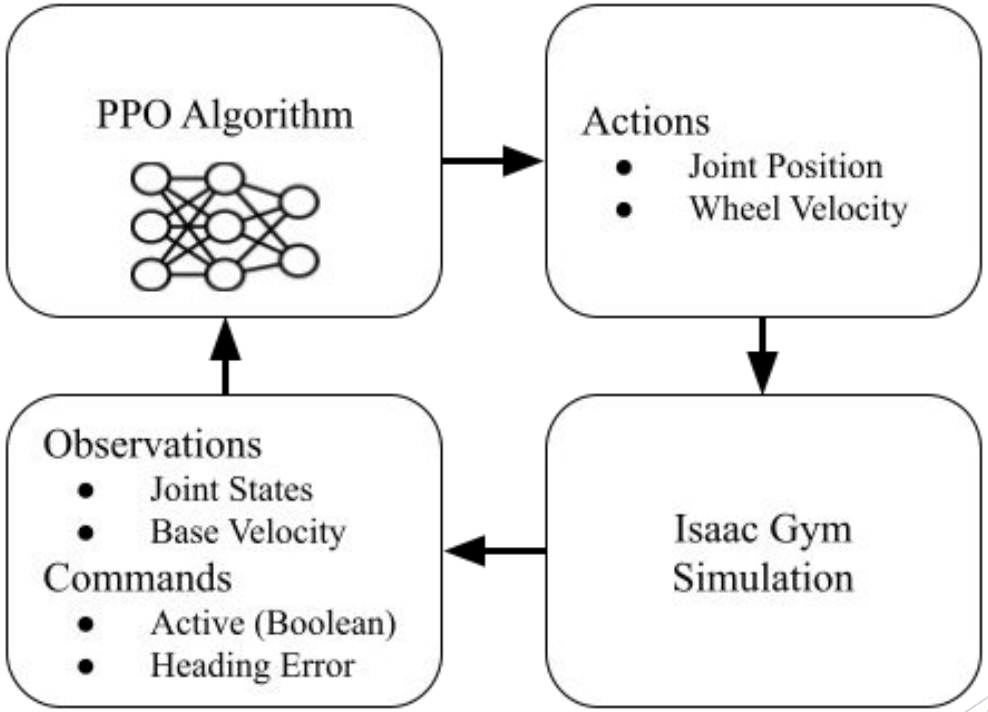
RL and Mixture of Experts

- Running on Flat Surface ≠ Climbing Stairs ≠ Navigating Rough Terrain

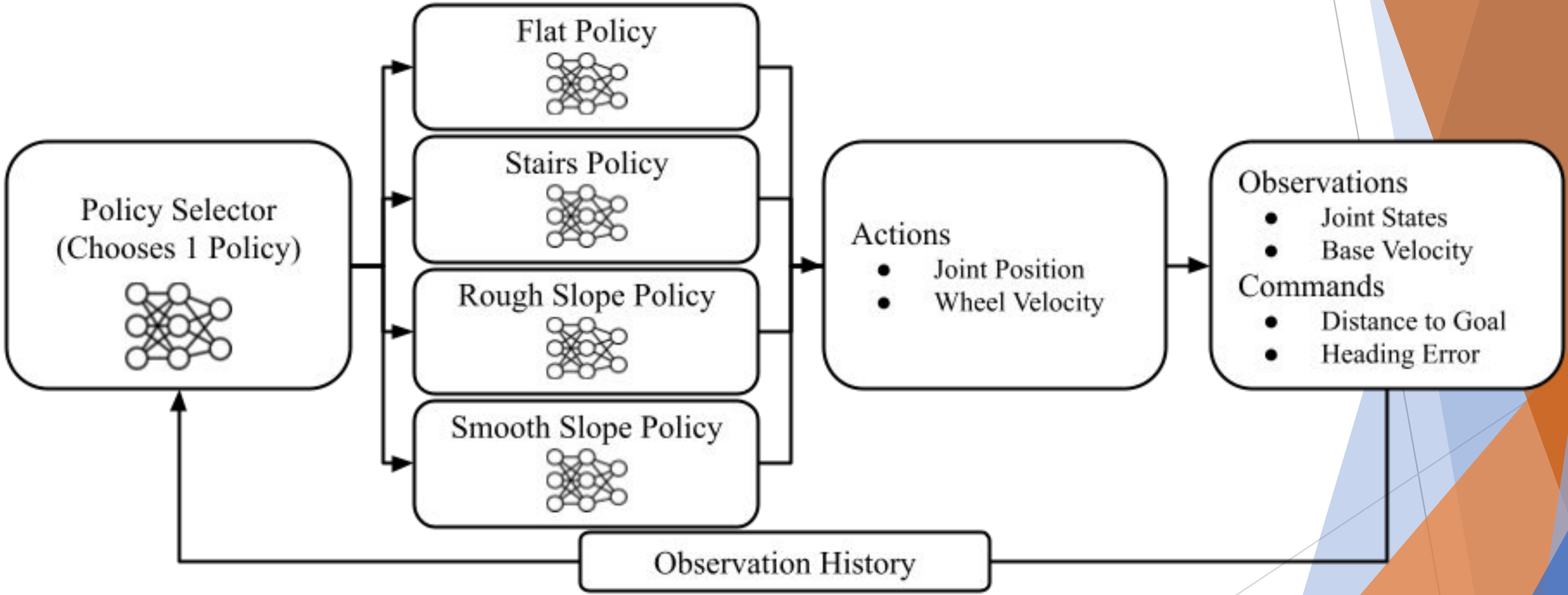


Training Structure

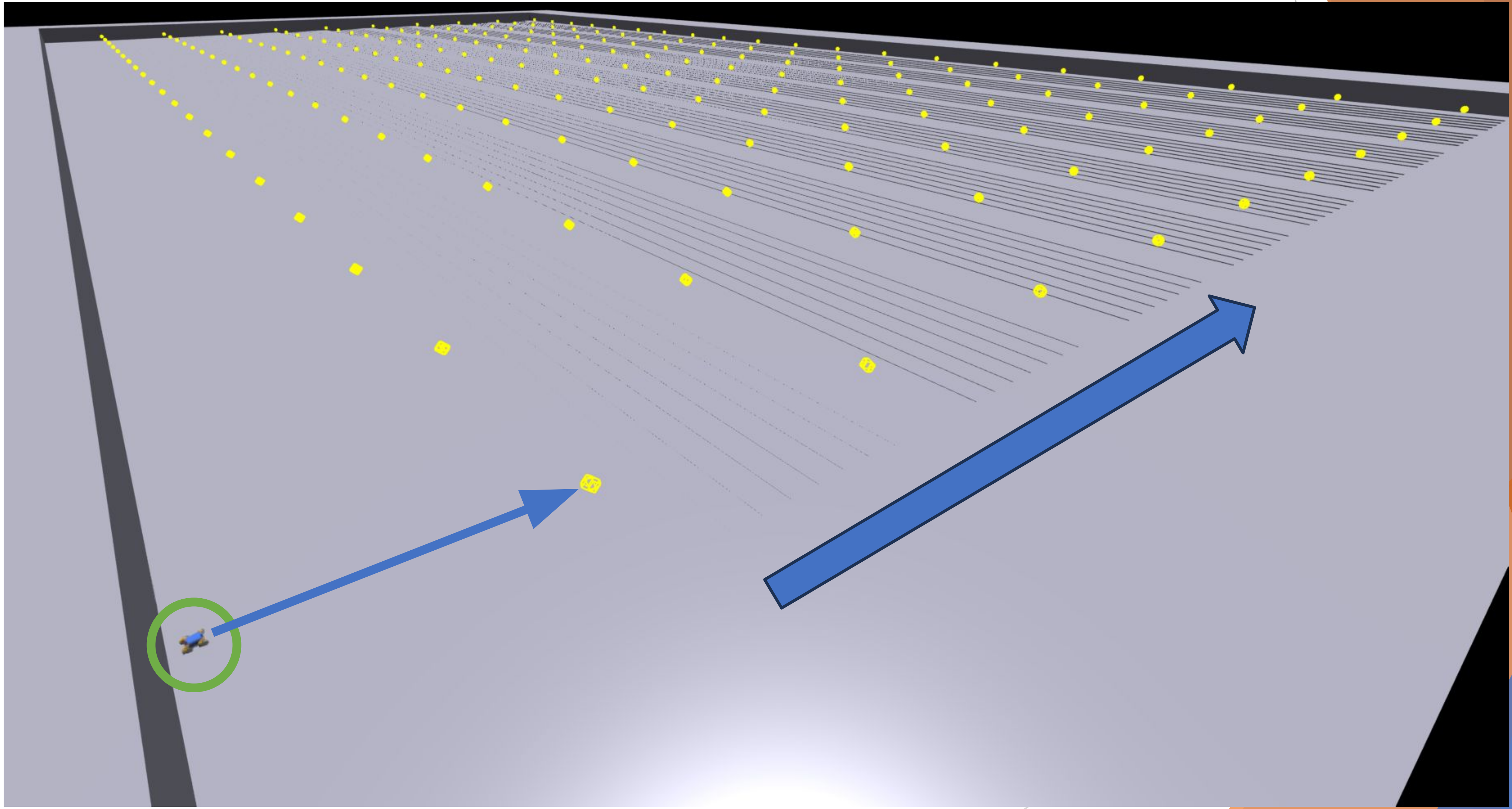




Deployment Structure



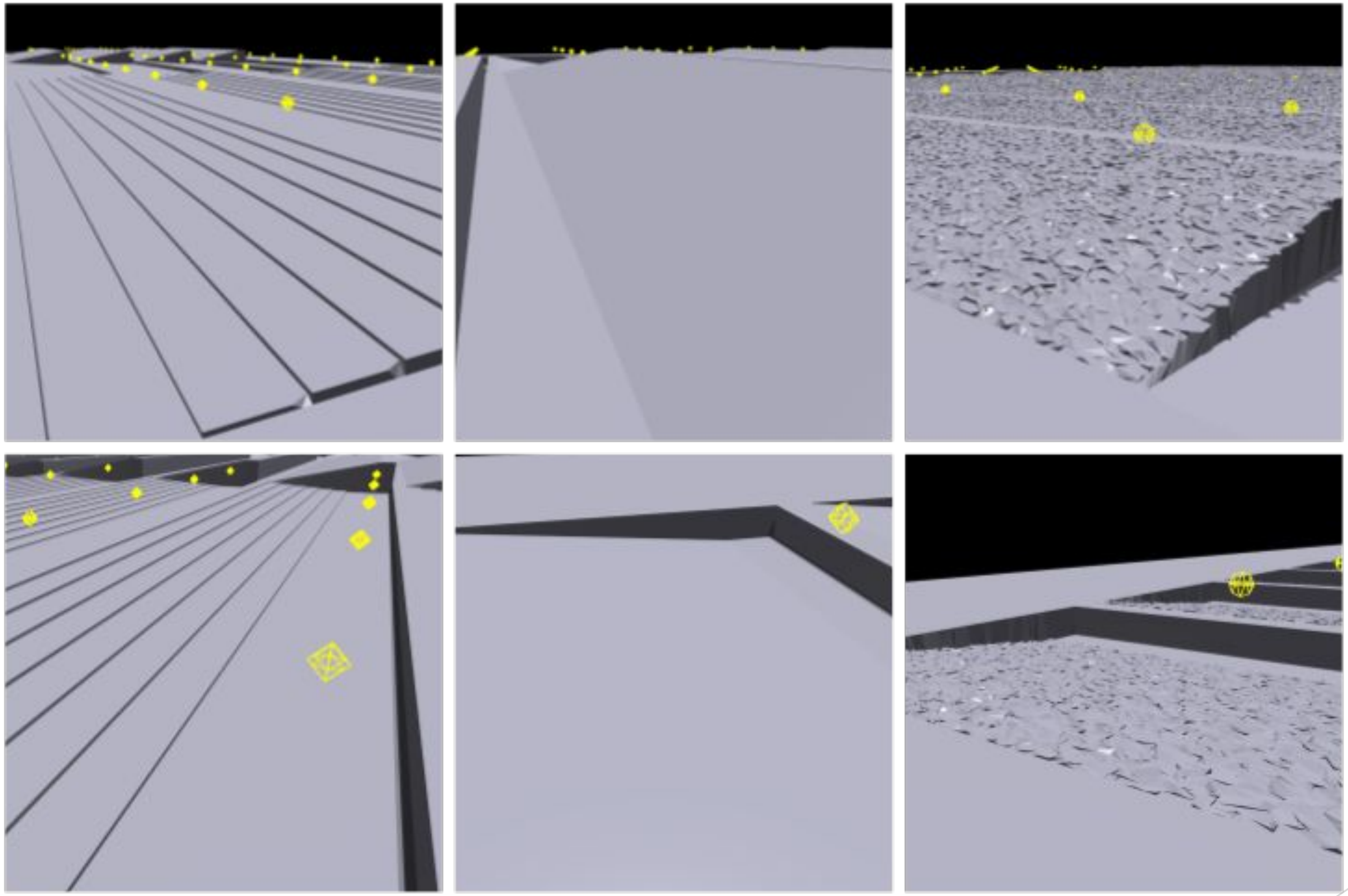
Training Environment



Rewards

Name	Formula	Coeff.
Proximity		0.01
Position		10
Heading		1
Positive End		10

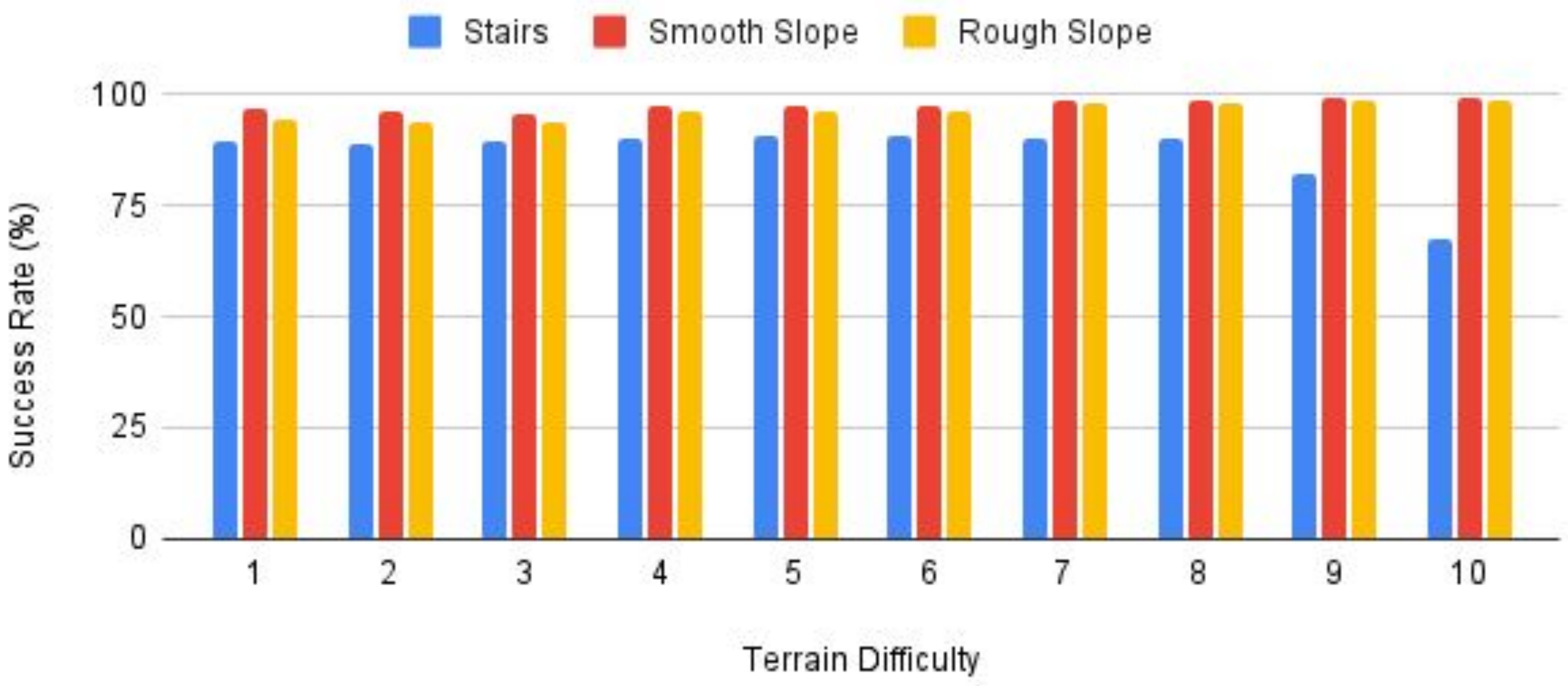
Environments



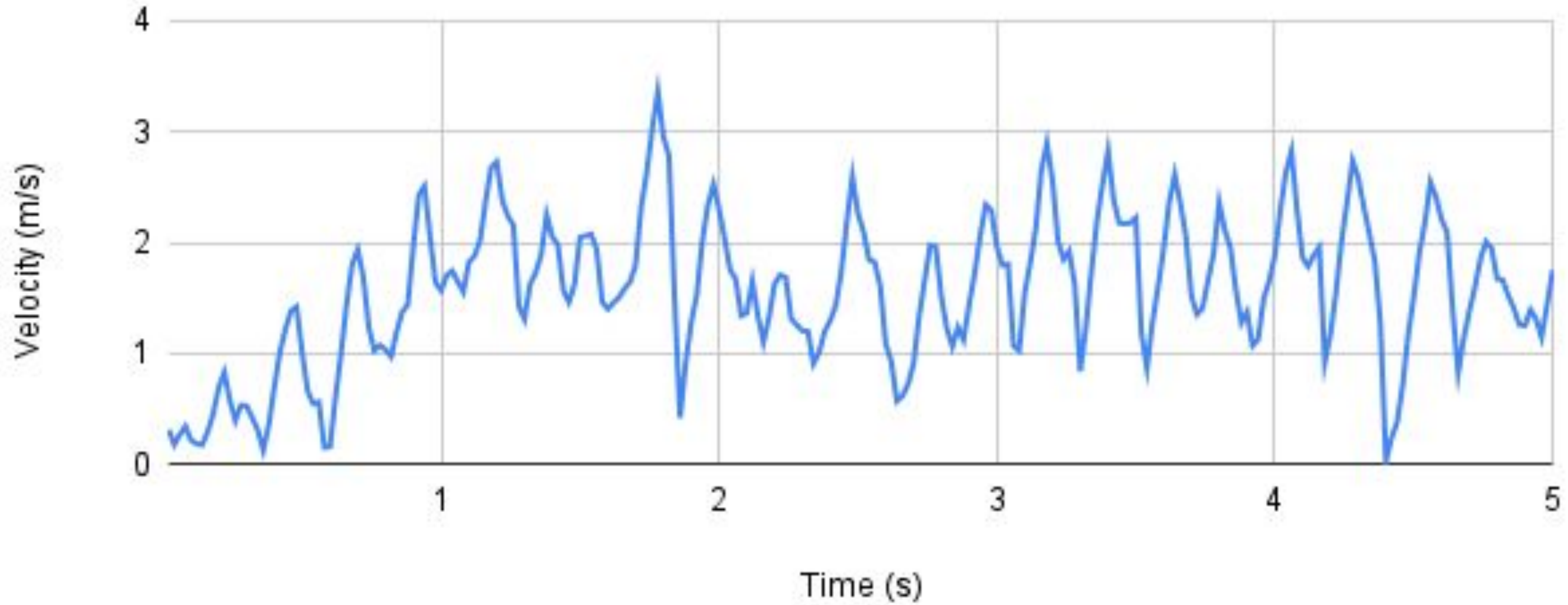
Terrain Difficulty

Difficulty Level	Stairs	Smooth slope	Rough Slope
	Step Height	Slope Angle	Slope Angle Randomized Height: ±5cm Variation
1	1 cm	0°	0°
2	2 cm	2.87°	2.87°
3	3 cm	4.30°	4.30°
4	4 cm	5.74°	5.74°
5	5 cm	7.18°	7.18°
6	6 cm	8.63°	8.63°
7	7 cm	10.1°	10.1°
8	8 cm	11.5°	11.5°
9	9 cm	13.00°	13.00°
10	10 cm	14.5°	14.5°

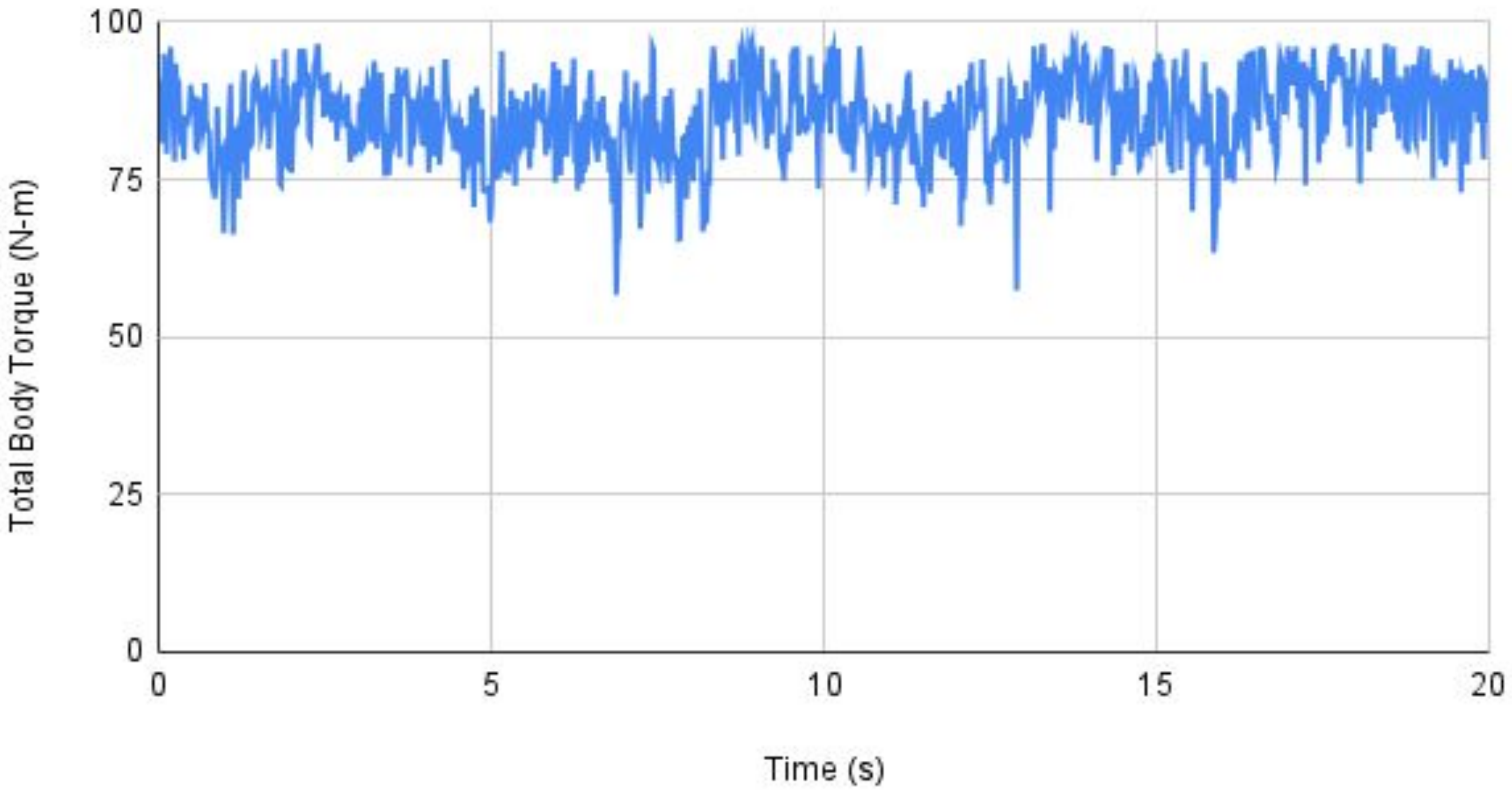
Success Rates Across Terrains



Speed



Efficiency



~0.25 Watts Per Meter on Stairs

Future Directions

- Validate performance in real-world environments, addressing the sim-to-real gap.
- Expand the mixture of experts system to include more complex terrains.
- Develop blind terrain mapping through touch.

Acknowledgement

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Thank You for Listening

Q&A